Model-Based Earnings Forecasts vs. Financial Analysts' Earnings Forecasts

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Abstract

Existing accounting-based forecasting models of earnings either do not fully consider information that is contained in stock prices or use an ad hoc specification that is not based on rigorous valuation theory. In this paper, we develop an earnings forecasting model built on the theoretical linkages between future earnings and stock prices as well as a number of accounting fundamental variables. We find that our model-based forecasts of earnings are in general less biased and more accurate than both existing model-based forecasts and analysts' consensus forecasts, at both shorter and longer horizons. We also show that the accuracy of both model-based forecasts and financial analysts' forecasts depend on firm-specific characteristics such as firm size and industry membership.

Keywords: Analysts' earnings forecasts, model-based earnings forecasts, forecast horizons, accuracy, incremental information, firm characteristics

1. Introduction

Forecasting earnings is of paramount importance in fundamental equity valuation and decision making in capital budgeting. The earnings forecasts issued by sell-side analysts have been widely used by both academics and practitioners, in spite of the fact that they have been shown to be upwardly biased. A natural question is whether there exists a superior alternative to analysts' earnings forecasts. Attention has therefore turned to developing models of individual companies' earnings that are able to generate forecasts of future earnings that are less biased and more accurate than those produced by analysts.

Existing accounting-based forecasting models of earnings either do not fully consider information that is contained in stock prices or use an ad hoc specification that is not based on rigorous valuation theory. In this paper, we develop an earnings forecasting model within the Pope and Wang (2005, PW) framework, which we use to generate forecasts of one- to five-year ahead earnings per share. The PW model includes stock prices, which are assumed to reflect all information that is available to market participants, as well as accounting accruals, which have been shown to be relevant in forecasting earnings over longer horizons. Given that a typical financial analyst concentrates on one or two specific industries, and that the existing literature documents that analysts' consensus forecasts outperform model-based forecasts in the short run, but tend to underperform them in the long run, we aim to answer the following three questions. First, can forecasts of earnings based on the PW model that incorporate information in stock prices and accounting accruals outperform those from financial analysts at shorter horizons as well as those from existing purely accounting-based models at longer horizons? Second, do analysts' consensus forecasts contain incremental information in explaining future earnings after controlling for model-based forecasts? Third, to what extent does earnings forecast accuracy depend on firm characteristics such as industry membership?

We show that the forecasts from the PW model are in general less biased and more accurate than the forecasts of professional analysts as well as existing model-based forecasts. Specifically, we show that short horizon forecasts based solely on historical accounting information can be improved by incorporating information contained in stock prices. At the one- and two-year horizons, the PW forecasts are significantly more accurate than all other forecasts. At the five-year horizon, the existing accounting-based forecasts perform as well as the PW forecasts, and both are superior to analysts' forecasts. This suggests that accounting information and market information have different roles in earnings forecasting, depending on the forecast horizon.

The apparent superiority of model-based earnings forecasts, however, does not necessarily mean that analysts' forecasts are redundant, since there is no reason a priori to assume that the information that they contain is fully subsumed by model-based forecasts. Consequently, analysts' forecasts could be expected to contain information about future earnings beyond that contained in the forecasts of accounting-based models. Therefore, in addition to using the conventional measures of bias and accuracy of forecasts of earnings, we also use encompassing tests to measure the *incremental* information content of competing forecasts and, in particular, to establish whether one forecasting model is encompassed by another. We use encompassing tests to measure the incremental information content of analysts' forecasts relative to the forecasts derived from an autoregressive model, the random walk model and accrual-based models, and find that analysts' forecasts are statistically and economically significant in explaining future earnings, even after controlling for the model-based forecasts, suggesting the usefulness of private information in earnings forecasting.

To shed further light on the determinants of earnings forecast accuracy and explanatory power over different forecast horizons, we examine the dependency of forecast bias and accuracy on various firm characteristics, such as industry membership, firm size, and the earnings-to-price (E/P) ratio. In particular, we investigate the circumstances under which financial analysts' forecasts outperform model-based forecasts. We show that there are systematic industry effects in forecast accuracy, with analysts' forecasts significantly more accurate than the PW forecasts for the financial and telecommunications industries, but significantly less accurate for others. We find that earnings forecasts from all sources are more accurate for large companies than for small companies at all forecast horizons. At the one- and two-year horizon, analysts' forecasts are significantly more accurate than all model-based forecasts for large firms and less accurate for small firms. However, at the five-year horizon, analysts' forecasts are less accurate than all model-based forecasts, except for those from the random walk model. We also find that analysts' forecasts are more accurate than all model-based forecasts, except the PW forecasts, for high E/P firms.

The remainder of the paper is organized as follows. Section 2 summarizes the relevant literature and develops testable hypotheses. Section 3 introduces the PW model and the empirical implementation of model-based forecasts. Section 4 describes the data used in the analysis and the estimation methodology. Section 5 evaluates the performance of the model-based earnings forecasts and financial analysts' consensus earnings forecasts, and establishes their incremental information content. Section 6 examines the relationship between forecast performance and firm characteristics. Section 7 offers some concluding comments.

2. Literature Review and Hypotheses Development

2.1 Literature Review

The consensus forecasts of earnings produced by financial analysts are widely used by both academics and the investment community, although there is extensive evidence that analysts' forecasts are systematically biased (see O'Brien 1988; Mendenhall 1991; Brown 1993; Das et al. 1998; Bradshaw et al. 2012; Lee and So 2017). Biases in analysts' forecasts potentially arise from a variety of conflicts of interest (see Francis and Philbrick 1993; Dugar and Nathan 1995; Lin and McNichols 1998; Ramnath et al. 2008). For example, it has been argued that analysts are reluctant to make negative recommendations about the stocks that they follow as this has an adverse impact on the commission that they receive (see Cowen et al. 2006; Irvine 2004; Jackson 2005). Becker (2001) also argues that investment bank analysts may generate positively biased forecasts in return for investment banking business. While recent regulation has attempted to restore the credibility of analyst research, it does not appear to have diminished the bias in their forecasts (see Guan et al. 2012).[2] As a result, recent research has focussed on model-based forecasts of earnings that are free of these biases, and a number of studies have shown that models that incorporate accounting information are able to generate forecasts of future earnings that are superior to the earnings forecasts issued by analysts in terms of the coverage of firms and unbiasedness, particularly at longer horizons.

Motivated by the increasing coverage of firms in analysts' forecasts, Hou et al. (2012, HDZ) develop a cross-sectional forecasting model of earnings based solely on a small number of accounting variables established from prior empirical findings. In particular, one-period ahead earnings are specified as a linear function of total assets, dividend payments, earnings and accruals as follows:

$$E_{j,t+1} = \gamma_{j0} + \gamma_{j1} A_{j.t} + \gamma_{j2} D_{j,t} + \gamma_{j3} DD_{j,t} + \gamma_{j4} E_{j,t} + \gamma_{j5} NegE_{j,t} + \gamma_{j6} AC_{j,t} + \varepsilon_{j,t+1}, \qquad (1)$$

where $E_{j,t}$ denotes the total earnings of firm *j* at time *t*, $A_{j,t}$ is total assets, $D_{j,t}$ is the total common dividend payment and $AC_{j,t}$ is total operating accruals. $DD_{j,t}$ is a dummy variable

[2] This is, however, balanced against the reputational cost of inaccuracy and thus in fact analysts face a trade-off (see Barber et al. 2007).

that equals 0 if the firm pays a dividend at time *t* and 1 otherwise, $NegE_{j,t}$ is a dummy variable that equals 1 if the firm has negative earnings at time *t* and 0 otherwise. HDZ employ their model to forecast the total earnings of individual firms, and find that their model produces earnings forecasts that are comparable to I/B/E/S consensus forecasts in terms of accuracy in the long run, but exhibit lower levels of bias.[3] They also note that their forecasts of earnings underperform consensus analyst forecasts at the one-year horizon.

The HDZ model has been used as a benchmark earnings forecasting model in the recent literature. For example, Li and Mohanram (2014) argue that the HDZ model does not always outperform a simple first order autoregressive (AR(1)) model, while Gerakos and Gramcy (2013) find that the HDZ model forecasts sometime underperform a naive random walk (RW) model, even though the HDZ model incorporates a larger information set than the AR(1) and RW models. Recently, Evans et al. (2017) also find that forecasts from their model, as well as forecasts from the HDZ, AR(1) and RW models, are all less accurate than consensus analyst forecasts at the one-year forecast horizon.

It may not be surprising that analysts' forecasts of earnings are more accurate than model-based forecasts at *shorter* horizons. On the one hand, analysts condition their expectations of future earnings on a much richer information set including not only accounting information, but also market and private information (Fried and Givoly 1982; Kross et al. 1990; Alford and Berger 1999; Sougiannis and Yaekura 2001). On the other hand, the existing accounting-based forecasting models of earnings either do not fully take into account information that is

[3] The HDZ model is used to generate forecasts of total earnings, while I/B/E/S reports analysts' forecasts of earnings per share. In order to make them comparable, HDZ scale the model-based forecasts of total earnings by the current market value of equity, and the analysts' forecasts of earnings per share by the current stock price. These are evaluated with respect to actual earnings from Compustat scaled by the market value of equity (for the model-based forecasts) and actual earnings per share from I/B/E/S scaled by the stock price (for analysts' forecasts).

contained in stock prices or select an ad hoc specification that is not based on valuation theory.[4]

The above accounting-based earnings forecasting models can be thought of as special cases of the generalized earnings forecasting framework of Richardson et al. (2010), in which expected one-period ahead earnings are specified as a function of current earnings, book value, changes in book value and a set of potentially useful non-accounting variables including variables such as the current market price of equity and the change in the market price. This specification captures a number of established features that have been reported in the literature. First, earnings are highly persistent (Fama and French 2006; Hou and Robinson 2006). Second, stock prices and returns are leading indicators of future earnings (Beaver et al. 1980; Beaver et al. 1987; Beaver et al. 1997; Weiss et al. 2008). This is also consistent with the observation that stocks are often valued based on the forward earnings-to-price (E/P) ratio. Third, changes in the book value of equity may reflect accounting conservatism, and so (lagged) book value may play a role in predicting future earnings (Feltham and Ohlson 1995; Pope and Wang 2005).

In Section 3, we develop a theoretical earnings model, which can be viewed as a parametric representation of the generalized earnings forecasting framework of Richardson et al. (2010).

2.2 Hypotheses Development

To shed further light on the determinants of earnings forecast accuracy over the different forecast horizons with respect to model-based forecasts and analysts' forecasts, we examine the relationship between forecast performance and industry membership, firm size, and the earnings-to-price ratio. First, since an individual analyst often follows one or two industries and some analysts' forecasts may be persistently more accurate than others, it is possible that

[4] Fama and French (2000, 2006) and So (2013) also develop cross-sectional models to forecast earnings by fitting one period ahead earnings to a few ad hoc firm characteristics such as current earnings, book values, accounting accruals, asset growth, dividends and stock price.

the I/B/E/S forecasts for some industries outperform the model-based forecasts. In addition, the characteristics of financial statements for some industries, such as the financial industry, are very different from other industries. Moreover, regulatory requirements also have a profound effect on financial statements in some industries. They pose challenges in forecasting future earnings using a mechanical model. Therefore the model-based forecasts may not necessarily be able to beat analysts' forecasts of earnings in these cases. Second, recent research documents that financial analysts' forecasting accuracy and coverage are related to firm size (Lee and So 2017). Since large companies tend to be followed by more analysts than small companies, we should expect that for large companies, analysts' consensus estimate of short term forecasts are more accurate than the corresponding model-based forecasts. Indeed, it is analysts' short termism that paves the way for the usefulness of model-based forecasts in the long run. Following the prior literature, firm size is measured by market capitalization, computed as the product of the price and the number of shares outstanding. Third, the price-to-earnings (P/E) ratio is the most widely used financial ratio by analysts. Equity research reports are often based upon the P/E multiple, which also forms the basis of value investing "screens".[5] The P/E ratio is believed to reflect market perceptions of the risk and future growth in earnings. A low P/E suggests that the market perceives the firm as higher risk or lower growth relative to a firm with a higher P/E. The analysts' consensus forecasts based on both public and private information should outperform the model-based forecasts for high risk firms. More importantly, analysts pay much more attention to low P/E firms, aiming to undercover undervalued stocks. Therefore, we expect the I/B/E/S consensus forecasts to be more accurate than model-based forecasts for low P/E (i.e. high E/P) firms. Based on the above analysis, we develop the following three hypotheses:

[5] For example, "We use P/E to derive our price target for Apple." (UBS, 6 November 2017); "Our $1,200 December 2018 price target is based on 24x our 2019E Alphabet GAAP EPS." (J.P. Morgan, 27 October 2017).

H1: Financial analysts' consensus forecasts are more accurate than model-based forecasts for industries with distinct characteristics in their financial statements.

H2: Financial analysts' consensus forecasts are more accurate than model-based forecasts for large firms.

H3: Financial analysts' consensus forecasts are more accurate than model-based forecasts for high E/P firms.

The results from testing these hypotheses are presented in Section 6.

3. Earnings Forecasting Models

3.1 A New Earnings Forecasting Model

The theoretical basis of the intrinsic relationship between future earnings and stock prices and other accounting fundamentals has recently been explored by Ashton and Wang (2013), who develop a theoretical earnings model in which one-period-ahead earnings are a function of current earnings, current and lagged book values of equity, and current and lagged market prices of equity.[6] However, they do not consider the role of earnings components such as accounting accruals in forecasting of future earnings. In contrast, HDZ is a pure accounting based cross-sectional forecast model, which does not incorporate market information. In this paper, we extend these models by incorporating an earnings component as well as stock prices, based on the Pope and Wang (2005, PW) model. Under the no-arbitrage assumption and clean surplus accounting, the Appendix shows the theoretical link between one period ahead forecasts of earnings and six observable accounting variables including earnings (e_t), current and lagged book value of equity (b_t), operating accruals (acc_t), and non-accounting

[6] The purpose of Ashton and Wang (2013) is to simultaneously estimate the implied cost of equity capital and the long-run growth rate. They use analysts' earnings forecasts as an input, but do not explore the earnings forecasting potential of their model.

variables including current and lagged stock price (P_t). For the purpose of presentation, we rewrite the model as:[7]

$$E_t[e_{t+1}] = \delta_1 P_t + \delta_2 e_t + \delta_3 b_t + \delta_4 b_{t-1} + \delta_5 P_{t-1} + \delta_6 acc_t. \tag{2}$$

Clearly this model is a formalization of the earnings forecasting framework of Richardson et al. (2010). Note that one can replace b_{t-1} by dividends using the clean surplus relation. If both sides of equation (2) are divided by book value, one can see that equation (2) is consistent with the model of Fama and French (2006), in which a number of accounting ratios including price-to-book, current profitability and dividend-to-book, are used to forecast future profitability. We refer to model (2) as the PW model and use it directly to forecast earnings.

3.2 Empirical Implementation of Model-Based Forecasts

We generate one-, two- and five-year ahead forecasts of earnings per share using the following pooled cross-section regression model based on the PW model:

$$e_{j,t+k} = \delta'_{0jk} + \delta'_{1jk} P_{j,t} + \delta'_{2jk} e_{j,t} + \delta'_{3jk} NegE_{j,t} + \delta'_{4jk} b_{j,t} + \delta'_{5jk} b_{j,t-1} + \delta'_{6jk} P_{j,t-1} + \delta'_{7jk} acc_{j,t} + \varepsilon_{j,t+k}, \tag{3}$$

for k = 1, 2, 5, where $e_{j,t}$ is the earnings per share of firm j in year t, $P_{j,t}$ is the stock price, $b_{j,t}$ is the book value of equity and $acc_{j,t}$ is operating accruals on a per share basis. $NegE_{j,t}$ is a dummy variable that equals 1 if the firm has negative earnings at time t and 0 otherwise.[8] We introduce this earnings dummy variable not only because negative earnings are less persistent, but also to make it comparable with the HDZ model. Note that the principle difference between the HDZ and PW models is that the former uses only historical

[7] The Ashton and Wang (2013) forecasting model is a special case when $acc_t = 0$.

[8] Using the clean surplus accounting identity, one can replace the lagged book value in equation (3) by dividends. This yields very similar results.

accounting variables, while the latter also includes non-accounting information in the form of the stock price.

Since I/B/E/S reports analysts' forecasts of earnings on a per share basis, in order to make the models comparable, we implement the HDZ model to forecast earnings *per share* rather than total earnings. In particular, we use the following regression to generate forecasts of one-, two- and five-year ahead earnings per share from the HDZ model:

$$e_{j,t+k} = \gamma_{0jk} + \gamma_{1jk} a_{j,t} + \gamma_{2jk} d_{j,t} + \gamma_{3jk} DD_{j,t} + \gamma_{4jk} e_{j,t} + \gamma_{5jk} NegE_{j,t} + \gamma_{6jk} acc_{j,t} + \varepsilon_{j,t+k}, \qquad (4)$$

for k = 1, 2, 5, where $e_{j,t}$, $a_{j,t}$, $d_{j,t}$ and $acc_{j,t}$ are, respectively, total earnings, total assets, total common dividends and total operating accruals of firm j at time t, deflated by the total number of shares outstanding at time t. $DD_{j,t}$ is a dummy variable that equals 1 for dividend payers and 0 otherwise. $NegE_{j,t}$ is a dummy variable that equals 1 if the firm has negative earnings at time t and 0 otherwise.

In addition to comparing the PW model with the HDZ model, we also follow prior literature and compare them both with the first order autoregressive (AR(1)) model and the random walk (RW) model, which simply sets future earnings to current earnings. In applying the AR(1) model, we use the following regression to generate forecasts of one-, two- and five-year ahead earnings per share:

$$e_{j,t+k} = \lambda_{0jk} + \lambda_{1jk} e_{j,t} + \lambda_{2jk} NegE_{j,t} + \varepsilon_{j,t+k}, \qquad (5)$$

for k = 1, 2, 5, where $e_{j,t}$ is the earnings per share of firm j in year t. $NegE_{j,t}$ is a dummy variable that equals 1 if the firm has negative earnings at time t and 0 otherwise.

4. Data and Estimation Methodology

4.1 Data

The sample covers the period July 1976 to June 2015, and comprises the intersection of the Center for Research in Security Prices (CRSP) monthly return file, the Compustat industrial annual file, and the Institutional Brokers Estimate System (I/B/E/S).[9] The adjusted numbers of shares outstanding, adjusted dividends at the end of the fiscal year, and adjusted prices of equity three months after the fiscal year end are collected from CRSP. The accounting variables are collected from Compustat. Following HDZ, prior to 1988, operating accruals are equal to the change in non-cash current assets less the change in current liabilities, excluding short-term debt and taxes payable, minus depreciation and amortization expense. Starting from 1988, accruals are the difference between earnings and cash flows from operations. Firms with negative book values are removed from the sample, and earnings are measured as net income before extraordinary items. Median consensus 1-, 2-, 3- and 4-year ahead forecasts of earnings per share and long run growth rates at the first month after the corresponding prior-year earnings announcements are obtained from I/B/E/S. Median consensus 5-year ahead forecasts are calculated by applying the analysts' forecasted long run growth rate from I/B/E/S to their 4-year ahead forecasts.[10] All accounting variables used in the analysis are divided by the adjusted number of shares to reduce heteroscedasticity and increase comparability across time. In constructing the data set, consistent with earlier research, we omit firms in the extreme percentile of earnings, book values, assets, prices, and one period ahead earnings forecasts, to reduce the effects of outliers (Ball et al., 2000). Firms

[9] I/B/E/S forecasts of earnings are available from 1976. The PW and HDZ models are estimated using a rolling window of ten years, and so we require data from CRSP and Compustat from 1962 in order to generate model-based forecasts of 3-year ahead earnings in 1976.

[10] The number of observations for three- and four-year ahead forecasts (which start only in 1985) is considerably smaller.

with a price per share less than $1 are also removed (Khan and Watts, 2009). Summary statistics of the dependent and independent variables are reported in Table 1.

< Insert Table 1 about here>

Panel A of Table 1 reports the mean, standard deviation, and the 25%, 50% and 75% quantiles of each series. On average, the I/B/E/S earnings forecasts are much higher than the realized earnings, reflecting the over-optimism of analysts' forecasts that is well documented in the literature. Panel B reports the average annual cross-sectional correlation matrix with Pearson (Spearman) correlations in the lower (upper) diagonals of the matrix for the full sample. Analysts' forecasts of earnings are highly positively correlated with current earnings, prices, book values, assets and dividends and negatively related to accounting accrual.

4.2 Estimation Methodology

We estimate the PW, HDZ and AR(1) models with pooled OLS using a rolling window of ten years. For each forecast year τ = 1976,…,2015, the model is estimated using only data that are available in year $\tau - k$, where k = 1, 2, 5 is the forecast horizon. The estimated coefficients from the pooled regression are then applied to the independent variables measured in year $\tau - k$ to generate out-of-sample k-year ahead forecasts of earnings for year τ.

5. Empirical Results

5.1 Earnings Model Estimation

Table 2 reports the time-series averages of the estimated coefficients and Newey-West adjusted t-statistics from the pooled estimation of the PW model, for the one-year to five-year forecast horizons.

<Insert Table 2 about here>

The PW model explains, on average, 41.7% of the variation in one-year ahead earnings, 24.2% of two-year ahead earnings and 12.2% of five-year ahead earnings. The adjusted R-squared falls with the forecast horizon, as expected. All variables and the intercept are significant at the one-, two- and three-year forecast horizons. All variables except prices are significant at the four- and five-year forecast horizons.

While the coefficient on lagged price is significantly negative at the one- to three-year forecast horizons, the coefficient on current price is significantly positive and decreasing as the forecast horizon increases. This suggests that prices (or, equivalently, returns) lead earnings after controlling for other accounting variables at least for the following three years. The forecasting ability of prices in earnings seems to be disturbed by the noise contained in stock prices in the long term. The coefficients on book value and lagged book value are, respectively, significantly negative and positive, and are similar in magnitude for each forecast horizon. Consistent with HDZ, the coefficient on accruals is significantly negative for all five forecast periods. The estimation results confirm that earnings are highly persistent, but that persistence decreases over time. The coefficients on earnings are positive and significant, indicating that current earnings are an important predictor of future earnings.

5.2 Forecast Performance

We now evaluate the earnings forecasts from the AR(1) model, HDZ model, PW model, RW model and I/B/E/S analysts' consensus forecasts, in terms of forecast bias and forecast accuracy. Following prior studies, forecast bias is defined as the mean difference between realized earnings and forecast earnings, scaled by price. Forecast accuracy is defined as the mean absolute value of the difference between realized earnings and forecast earnings, scaled by price.

Table 3 reports the forecast bias and forecast accuracy measured across firms over the sample period, for the one-, two- and five-year forecast horizons.

<Insert Table 3 about here>

For the one-year ahead forecasts, Panel A1 of Table 3 reports the bias and accuracy as well as their standard deviations and number of observations, while Panel A2 reports the pairwise t-tests for the forecast accuracy across different models. Panel A1 shows that the PW model and RW model have the lowest bias (-0.004 and 0.004, respectively), followed by the HDZ model (-0.005), AR(1) model (-0.013), and then the I/B/E/S consensus forecasts (-0.040). Among five forecasts, only the RW model underestimates realized earnings. Panel A1 of Table 3 also shows that the one-year ahead forecasts based on the PW model are more accurate than the I/B/E/S consensus forecasts and those from the other models. The mean absolute forecast error is 0.060, followed by the I/B/E/S consensus forecasts and the HDZ model (with a mean absolute forecast error of 0.063), then the AR(1) model and RW model (with a mean absolute forecast error of 0.065 and 0.068 respectively). In Panel A2, the pairwise t-tests show that these differences of accuracy are statistically significant except for the difference between the I/B/E/S consensus forecasts and the HDZ forecasts.

For the two-year ahead forecasts (Panels B1 and B2), again the PW model has the lowest bias (-0.000) and highest accuracy (0.069), followed by the HDZ model (with bias of -0.001 and accuracy of 0.071), then the AR(1) model (with bias of -0.011 and accuracy of 0.073). The forecast biases from the RW model and the I/B/E/S consensus forecasts are 0.015 and -0.046, respectively. However, the I/B/E/S consensus forecasts are more accurate than those from the RW model (with a mean absolute forecast error of 0.074 and 0.080 respectively). The pairwise t-tests show that these differences in forecast accuracy are statistically significant.

For the five-year ahead forecasts (Panels C1 and C2), the AR(1) model, HDZ model and PW model all have the same forecast bias of 0.020, followed by the RW model and the I/B/E/S forecasts. Only I/B/E/S forecasts show an upward bias at the five-year horizon. Panel C2 shows that the forecast accuracy of the PW model (0.070) is the same as that of the HDZ model. The pairwise t-tests show that both models are significantly more accurate than I/B/E/S consensus forecasts and forecasts from the AR(1) and RW models, while the difference in forecast accuracy between the PW and HDZ models is only marginal.

Our findings therefore suggest that the PW model-based forecasts of future earnings are significantly less biased and more accurate than analysts' forecasts at both short and long horizons. They also suggest that the PW model outperforms other model-based forecasts. Thus it would appear that market information has an incremental role over accounting information, particularly in the short term. Table 3 also shows that the standard deviations of bias and accuracy from the PW model forecasts are smaller than those for other forecasts, at all forecast horizons. Although analysts condition their expectations of future earnings on a richer information set, they have a tendency to concentrate on short term earnings forecasts and analysts' private information aggregated in the consensus forecasts may thus help to improve their accuracy over short horizons.[11] This is reflected in our findings, which show that analysts' forecasts are more accurate than all model-based forecasts, except the PW model, at one-year horizon. The accrual variable included in both the PW and HDZ models is evidently useful for forecasting earnings over longer horizons. This is perhaps because accruals, as a component of earnings, are used to smooth cash flows over time. For example,

[11] This is partly because of the inherent challenges in forecasting earnings over longer horizons and analysts' private information offset perhaps by conflicts of interests and other sources of noise, which serve to reduce their usefulness over time. It is also consistent with the focus on short term earnings by financial managers and investors. Rappaport (2005) argues that short term earnings fuel stock price changes. The high turnover of professionally managed funds is closely related to short term earnings forecasts since the average holding period of the funds is less than one year. In addition, investment managers who are able to consistently and accurately forecast short term earnings often gain abnormal returns.

investment expenses can be deferred over a number of years and deferred expenses affect future earnings.

5.3 Efficiency and Encompassing Tests

We now evaluate the efficiency of the AR(1), HDZ, PW, RW model-based forecasts and I/B/E/S consensus forecasts, and examine the *incremental* information that they contain about realized earnings. An earnings forecast is efficient if it optimally reflects currently available information, and is therefore associated with a forecast error that is unpredictable. In its weakest form, this requires that the forecast error is uncorrelated with the earnings forecast itself. Weak efficiency is tested by estimating the following Mincer-Zarnowitz (1969) regression:

$$e_{j,t+1} = \alpha + \beta \hat{e}_{j,t} + v_{j,t+1} \tag{6}$$

where $\hat{e}_{j,t}$ is the forecast made at time t of the earnings of firm j at time t+1, α and β are intercept and slope coefficients, respectively, and $v_{j,t+1}$ is a zero mean error term. If the earnings forecasts are weakly efficient, the slope coefficient, β, should be close to one. If β is significantly different from one then conditioning on the forecast itself, the forecast error is predictable. The R-squared statistic from the Mincer-Zarnowitz regression measures the information content of the forecasts, irrespective of their bias and inefficiency.

Panel A of Table 4 reports the results of estimating the Mincer-Zarnowitz regression for the one-year ahead AR(1), HDZ, PW, RW forecasts and the I/B/E/S consensus forecasts. For all forecasts with the exception of those from the RW model, the slope coefficient is close to one. Thus, the model-based forecasts have similar efficiency compared to analysts' forecasts. The R-squared statistics reveal that of the four model-based forecasts, the PW forecasts are more informative than the AR(1), HDZ and RW forecasts (with R-squared coefficients of 41.6%, 37.8%, 39.1% and 36.3%, respectively). Moreover, the model-based forecasts are significantly more informative than the I/B/E/S consensus forecasts (with an R-squared coefficient of 33.0%).

Panels B and C of Table 4 reveal that, as the forecast horizon increases, the information content of all five forecasts falls. However, the reduction for the I/B/E/S consensus forecasts is much greater than it is for the AR(1), HDZ, PW and RW model-based forecasts: at the two-year horizon (Panel B), the R-squared coefficient for the AR(1), HDZ, PW, RW and I/B/E/S forecasts is 20.5%, 22.8%, 22.8%, 19.6% and 14.1%, respectively, while at the five-year horizon (Panel C), it is 7.0%, 10.4%, 9.4%, 6.9% and 5.3%. While the PW forecasts are more informative than the HDZ forecasts over the one-year horizon, the HDZ forecasts are marginally more informative than the PW forecasts over the five-year horizon.

<Insert Table 4 about here>

The Mincer-Zarnowitz regression can also be used to measure the incremental information content of competing forecasts, irrespective of their bias and accuracy, and whether one forecasting model is encompassed by another. In particular, we can estimate the following regression of realized earnings on *K* competing forecasts $\hat{e}^1_{j,t},\ldots,\hat{e}^K_{j,t}$:

$$e_{j,t+1} = \alpha + \beta_1 \hat{e}^1_{j,t} + \ldots + \beta_K \hat{e}^K_{j,t} + v_{j,t+1} \tag{7}$$

If β_K =0 then the forecasts from model *k* do not contain any information about realized earnings beyond that contained in the other models, and so the other models encompass model *k*. More generally, the relative magnitude and statistical significance of the coefficients $\beta_1,\ldots,\beta_K$ measure the relative information content of the competing forecast series. Since the RW forecasts are less informative than other model-based forecasts from the above analysis and existing literature, we omit the RW forecasts in the following encompassing tests for tractability.

Table 5 reports the results of estimating the encompassing regressions for the AR(1) and HDZ forecasts (Model 1), the AR(1) and PW forecasts (Model 2), the AR(1) and I/B/E/S forecasts (Model 3), the HDZ and PW forecasts (Model 4), the HDZ and I/B/E/S forecasts (Model 5), the PW and I/B/E/S forecasts (Model 6), the AR(1), HDZ and PW forecasts (Model 7), the AR(1), HDZ and I/B/E/S forecasts (Model 8), the HDZ, PW and I/B/E/S forecasts (Model 9) and the AR(1), HDZ, PW and I/B/E/S forecasts (Model 10). The encompassing regressions are estimated for the one-, two- and five-year forecast horizons. At the one-year horizon (Panel A), the AR(1) forecasts are not significant only when the PW forecasts are included in the regressions. While the PW forecasts and HDZ forecasts individually contain similar information about one-year ahead earnings, both remain significant when included simultaneously (Model 4), but the PW forecasts dominate the HDZ forecasts in terms of the magnitude of the slope coefficient and its significance. Combining the I/B/E/S consensus forecasts with any model-based forecasts significantly reduces the importance of the I/B/E/S consensus forecasts, suggesting that the model-based forecasts contain much of the information that is contained in analysts' forecasts. However, the analysts' consensus forecasts are not redundant after controlling for the model-based forecasts. Almost the highest adjusted R-squared is obtained by combining just the PW forecasts and the I/B/E/S consensus forecast (Model 6). When all forecasts are included (Model 10), the PW forecasts dominate, followed by the I/B/E/S consensus forecasts. Indeed, after accounting for both the PW forecasts and the I/B/E/S consensus forecast, the HDZ forecasts contain no incremental information. At the two-year horizon (Panel B), again the AR(1) forecasts are not significant if the PW forecasts are included in the regressions. The PW and HDZ forecasts have similar incremental information content, both with respect to each other and with respect to I/B/E/S forecasts and the AR(1) forecasts. At the five-year horizon (Panel C), the HDZ, PW forecasts and the I/B/E/S forecasts are significant when all four forecasts are included in the encompassing regression.

The encompassing tests therefore suggest that the PW model generates forecasts that are the most informative at the one-year horizon. At the two- and five-year horizon, the HDZ forecasts, PW forecasts and the I/B/E/S forecasts all have incremental information content. Analysts' forecasts contain useful information, including their private information about future earnings, beyond that contained in model-based forecasts, although analysts' forecasts are less significant than both PW forecasts and HDZ forecasts.

A natural corollary of these findings is that the optimal forecast of future earnings conditioning on analysts' forecasts and model-based forecasts is likely to be a combination of the two, and this combination would depend on the forecast horizon. In the linear framework, the form of this optimal combination is provided by the estimated parameters of the encompassing regression, which also serves to correct for bias and inefficiency in the raw forecasts. In particular, at the one-year horizon, the optimal combination of forecasts would give weights to the PW forecasts and I/B/E/S consensus forecasts of about 79.8% and 30.7%, respectively (Model 6). At the two-year horizon, the optimal combination of forecasts would give weights to the HDZ forecasts, PW forecasts and I/B/E/S consensus forecasts of about 48.8%, 42.2% and 14.2%, respectively (Model 9), and at the five-year horizon, the weights would be 56.4%, 50.9% and 11.6% respectively (Model 10).

<Insert Table 5 about here>

6. Forecast Performance and Firm Characteristics

In this section, we test the hypotheses developed in Section 2 concerning the relationship between forecast performance and industry membership, firm size, and the earnings-to-price ratio. We first divide the full sample into 12 industries using the classification from Ken French's website, and then re-estimate each model for each industry.[12] Table 6 reports the mean absolute error of the AR(1), HDZ, PW, RW and I/B/E/S forecasts for each industry. At the one-year horizon, Panel A shows that analysts' forecasts are more accurate than all model-based forecasts, except the PW forecasts, for 10 out of 12 industries. At the one- and two-year horizon, the PW forecasts are at least as accurate as the I/B/E/S consensus forecasts for all but two industries: industry 7 (telecommunications) and industry 11 (finance). For industry 7, forecasting accuracy of the PW forecasts and analysts' forecasts are 0.059 vs. 0.053 and 0.063 vs. 0.061 for one- and two-year horizons, respectively. It may not be surprising since the telecommunication industry is widely regarded as having a lack of regulatory certainty. For the financial industry (#11), forecasting accuracy of the PW forecasts and analysts' forecasts are 0.059 vs. 0.055 and 0.067 vs. 0.062 for one- and two-year horizons, respectively. The PW forecasts are more accurate than all other model-based forecasts across all industries. At the five-year horizon, Panel C shows that the I/B/E/S consensus forecasts are still the most accurate forecasts for industry 11 (finance) with forecasting accuracy of 0.065. Therefore, the evidence in Table 6 supports our Hypothesis 1.

<Insert Table 6 about here>

In Table 7, we examine the relationship between forecast performance and firm size. Each year, the full sample of firms is sorted into deciles in order of market capitalization. Each model is then re-estimated and the analysis is conducted on all firms in each size decile for which analysts' forecasts are available. Table 7 reports the mean absolute error of the AR(1),

[12] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

HDZ, PW, RW and I/B/E/S forecasts, for each of one-, two- and five-year forecast horizons, by firm size. As expected, earnings forecasts from all sources are more accurate for large companies than for small companies at all three forecast horizons. This may reflect the high quality of financial reporting used in the model-based forecasts for large firms, which are more likely to be fairly priced. Analysts' forecasts are more accurate than all model-based forecasts for large firms from size decile 5 at the one-year horizon (Panel A), and from size decile 8 at the two-year horizon and less accurate for small firms (Panel B). The PW forecasts are more accurate than all other forecasts in the remaining size deciles. At the five-year horizon, Panel C shows that the two models that incorporate accounting accruals in general generate more accurate forecasts of earnings. Table 7 largely supports our Hypothesis 2.

<Insert Table 7 about here>

Table 8 reports the mean absolute error of the AR(1), HDZ, PW, RW and I/B/E/S forecasts for each of the one-, two- and five-year forecast horizons for deciles sorted by the E/P ratio each year. Each model is then re-estimated and the analysis is conducted on all firms in each E/P decile for which analysts' forecasts are available. At the one- and two-year horizons, Panels A and B show that the I/B/E/S forecasts are the second most accurate forecasts from E/P decile 5 to decile 10. The PW forecasts are more accurate than all other forecasts. At the five-year horizon, Panel C shows that the PW forecasts are also more accurate than other forecasts, except for very high E/P firms (deciles 9 and 10), where the I/B/E/S forecasts are more accurate. It is perhaps not surprising that the PW forecasts in general outperform all other forecasts including the I/B/E/S consensus forecasts since the PW model is the only model that can be converted to forecast the E/P ratio in terms of other accounting ratios. The evidence in Table 8 partially supports our Hypothesis 3.

<Insert Table 8 about here>

7. Concluding Remarks

Forecasts of earnings per share are an important input to fundamental equity analysis and investment decision making. It is well known that the widely used analysts' forecasts of earnings are systematically biased. Recent advances in the academic literature have shown that forecasts of future earnings based solely on accounting information, in particular accounting accruals, are superior to the earnings forecasts issued by sell-side analysts in terms of the coverage of firms and biasness at longer horizons. At the same time, analysts' forecasts contain information about future earnings beyond that contained in model-based forecasts and outperform the existing model-based forecasts at shorter horizons. This of course reflects analysts' short termism as is well documented in prior studies.

In this paper, we develop an earnings forecasting model built on the intrinsic relationships between future earnings and stock prices as well as a small number of accounting variables including operating accruals. We evaluate analysts' forecasts and the forecasts derived from four benchmark earnings models: the first order autoregressive (AR(1)) model, the random walk (RW) model, the HDZ model that is based on only historical accounting information,, and the PW model that includes stock prices and accounting information.

We show that the forecasts from the PW model in general outperform the forecasts of professional analysts as well as other model-based forecasts in terms of unbiasedness and accuracy, at both shorter and longer horizons. Our results suggest that the existing accounting model-based forecasts can be improved by incorporating market information at shorter horizons. In particular, the PW forecasts outperform the HDZ forecasts at the one- and two-year horizons. At the five-year horizon, the PW forecasts are as accurate as the HDZ forecasts. The forecasts based on models, in particular, the models including accounting accruals, outperform I/B/E/S consensus forecasts over longer horizons. The AR(1) and RW forecasts underperform the PW forecasts at all forecast horizons. Further, they have no incremental information relevant for explaining future realized earnings after controlling for the PW forecasts. Encompassing tests nevertheless show that analysts' forecasts of earnings are statistically and economically significant predictors of future earnings even after controlling for model-based forecasts.

We also show that forecasting accuracy of future earnings is associated with various firms characteristics. First, analysts' forecasts outperform all model-based forecasts in the financial industry at all forecast horizons. Second, earnings forecasts from all sources are more accurate for large companies than for small companies in both short- and long-term forecasting. Finally, I/B/E/S consensus forecasts are generally more accurate than model-based forecasts, except the PW forecasts, for firms with high earnings-to-price ratio.

References

Alford A. and P. Berger. 1999. “A Simultaneous Equations Analysis of Forecast Accuracy, Analyst Following, and Trading Volume.” *Journal of Accounting, Auditing & Finance* 14(3): 219-240.

Ashton, D. and P. Wang. 2013. “Terminal Valuation, Growth Rates and the Implied Cost of Capital.” *Review of Accounting Studies* 18 (1): 261-290.

Ball, R., S.P. Kothari and A. Robin. 2000. “The Effect of International Institutional Factors on Properties of Accounting Earnings.” *Journal of Accounting and Economics* 29: 1–51.

Barber, B. M., R. Lehavy and B. Trueman. 2007. “Comparing the Stock Recommendation Performance of Investment Banks and Independent Research Firms.” *Journal of Financial Economics* 85: 490-517.

Beaver, W., R. Lambert and D. Morse. 1980. “The information content of security prices.” *Journal of Accounting and Economics* 2: 3-28.

Beaver, W., R. Lambert and S. Ryan. 1987. “The information content of prices: A second look.” *Journal of Accounting and Economics* 9: 139-158.

Beaver, W., M. McAnally and C. Stinson. 1997. “The information content of earnings and prices: A simultaneous equations approach.” *Journal of Accounting and Economics* 23: 53-81

Becker, D. (2001, August 7). Analyzing analysts. Remarks before the Committee on Federal Regulation of Securities of the American Bar Association. Retrieved from ttp://www.sec.gov/ news/speech/spch510.htm.

Bradshaw, M., M. Drake, J. Myers and L. Myers. 2012. “A Re-examination of Analysts’ Superiority over Time-Series Forecasts of Annual Earnings.” *Review of Accounting Studies* 17: 944-968.

Brown, L. 1993. “Earnings forecasting research: It’s implications for capital markets research.” *International Journal of Forecasting* 9: 295–320.

Brown. L., B. Gay, and M. Turac. 2008. “Creating a “Smart” Conditional Consensus Forecast.” *Financial Analysts Journal* 64(6):74-86

Brown, L., G. Richardson and S. Schwager. 1987. “An information interpretation of financial analyst superiority in forecasting earnings.” *Journal of Accounting Research* 25: 49−67.

Cowen, A., B. Groysberg and P. Healy. 2006. "Which types of analyst firms are more optimistic?" *Journal of Accounting and Economics* 41: 119-146.

Das, S., B. Levine, and K. Sivarmakrishnan. 1998. "Earnings Predictability and Bias in Analysts' Earnings Forecasts." *The Accounting Review* 73: 277–94.

Dugar, A., and Nathan, S. 1995. "The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations." *Contemporary Accounting Research,* 12(1): 131–160.

Evans M, K. Njoroge and K. Ow Yong. 2017. "An Examination of the Statistical Significance and Economic Relevance of Profitability and Earnings Forecasts from Models and Analysts." *Contemporary Accounting Research,* forthcoming.

Fama, E. and K. French. 2000. "Forecasting profitability and earnings." *Journal of Business* 73(2):161–175.

Fama, E. and K. French. 2006. "Profitability, Investment and Average Returns." *Journal of Financial Economics* 82: 491-518.

Feltham, G. and J. Ohlson. 1995. "Valuation and Clean Surplus Accounting for Operating and Financial Activities." *Contemporary Accounting Research,* 11: 689-732.

Francis, J., and D. Philbrick. 1993. "Analysts' decisions as products of a multi-task environment." *Journal of Accounting Research* 31(2): 216–230.

Fried, D., and D. Givoly. 1982. "Financial Analysts' Forecasts of Earnings: a Better Surrogate for Market Expectations." *Journal of Accounting and Economics* 4(2): 85-107.

Gerakos, J. and R. Gramacy. 2013. "Regression-based Earnings Forecasts." Working paper, University of Chicago.

Guan, Y., H. Lu and M.H. Wong. 2012. "Conflict-of-Interest Reforms and Investment Bank Analysts' Research Biases." *Journal of Accounting, Auditing & Finance* 27(4): 443–470.

Hou, K., and D. Robinson. 2006. "Industry concentration and average stock returns." *Journal of Finance* 61: 1927-1956.

Hou, K., M. van Dijk, and Y. Zhang. 2012. "The Implied Cost of Capital: A New approach." *Journal of Accounting & Economics* 3(3): 504-526.

Irvine, P. J. 2004. "Analysts' forecasts and brokerage-firm trading." *Accounting Review* 79: 125-149.

Jackson, A. 2005. “Trade generation, reputation, and sell-side analysts.” *Journal of Finance* 60: 673-717.

Khan, M. and R. Watts. 2009. “Estimation and Validation of a Firm-year Measure of Conservatism.” *Journal of Accounting and Economics* 48: 132–50.

Kross, W., B. Ro and D. Schroeder. 1990. “Earnings Expectations: the Analysts’ Information Advantage.” *The Accounting Review* 65(2): 461-476.

Lee, C. M. and So, E. C. 2017. “Uncovering expected returns: Information in analyst coverage proxies.” *Journal of Financial Economics* 124(2):331–348.

Li, K. and P. Mohanram. 2014. “Evaluating cross-sectional forecasting models for implied cost of capital.” *Review of Accounting Studies* 19(3): 1152-1185.

Lin, H., and McNichols, M. 1998. “Underwriting relationships, analysts’ earnings forecasts and investment recommendations.” *Journal of Accounting and Economics,* 25(1), 101–127.

Mendenhall, R. 1991. “Evidence on the Possible Underweighting of Earnings Information.” *Journal of Accounting Research* 29: 170–9.

Mincer J. and Zarnowitz, V. 1969. “The evaluation of economic forecasts” in J. Mince ed., *Economic Forecasts and Expectation*, National Bureau of Research, New York.

O’Brien, P. 1988. “Analysts’ Forecasts as Earnings Recommendations.” *Journal of Accounting & Economics* 10: 53–83.

Ohlson, J. 1995. “Earnings, Book Values, and Dividends in Equity Valuation.” *Contemporary Accounting Research* 11(2): 661–87.

Pope, P. and P. Wang. 2005. “On the Relevance of Earnings Components: Valuation and Forecasting Links.” *Review of Accounting Studies* 10(4): 387-407.

Ramnath S., S., Rock and P. Shane. 2008. “The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research.” *International Journal of Forecasting* 24: 34-75.

Rappaport A. 2005. “The Economics of Short-Term Performance Obsession.” *Financial Analysts Journal* 61(3): 65-79.

Richardson, S., I. Tuna and P. Wysocki. 2010. “Accounting Anomalies and Fundamental Analysis: A Review of Recent Research Advances.” *Journal of Accounting and Economics* 50: 410-454.

So E.C. 2013. “A new approach to predicting analyst forecast errors: Do investors over weight analyst forecasts.” *Journal of Financial Economics* 108: 615–640

Sougiannis T. and T. Yaekura. 2001. “The accuracy and bias of equity values inferred from analysts' earnings forecasts.” *Journal of Accounting, Auditing & Finance* 16(4): 331-362.

Weiss, D., P.A. Naik and C.L. Tsai. 2008. “Extracting Forward-looking Information from Security Price: A New Approach.” *The Accounting Review* 83: 1101–1124.

Appendix: A New Earnings Forecasting Model

Our new earnings forecasting model builds on the Pope and Wang (2005) model, which extends the Ohlson (1995) model by incorporating accounting conservatism and an earnings component. Specifically, price of equity (P_t) is written in terms of book value (b_t), abnormal earnings (x_t^a) and an earnings component (x_{2t}): $P_t = b_t + \alpha_1 b_{t-1} + \alpha_2 x_t^a + \alpha_3 x_{2t}$, where abnormal earnings $x_t^a = e_t - (R-1)b_{t-1}$, e_t is earnings, and $R-1$ is cost of capital. By incorporating the "other information" variable introduced in Ashton and Wang (2013), we have the following equation system:

$$\begin{aligned} P_t &= b_t + \alpha_1 b_{t-1} + \alpha_2 x_t^a + \alpha_3 x_{2t} + v_t, \\ v_{t+1} &= \gamma_1 v_t + \gamma_2 (P_t + d_t - P_{t-1} - e_t) + \varepsilon_{t+1}, \end{aligned}$$

where "other information" (v_t) is assumed to be the value of future growth that has not yet been captured by the current accounting system.

Assume clean surplus accounting: $b_t = b_{t-1} + e_t - d_t = Rb_{t-1} + x_t^a - d_t$, we have

$$P_{t+1} + d_{t+1} = b_{t+1} + d_{t+1} + \alpha_1 b_t + \alpha_2 x_{t+1}^a + \alpha_3 x_{2t+1} + v_{t+1} = Rb_t + \alpha_1 b_t + (1+\alpha_2) x_{t+1}^a + \alpha_3 x_{2t+1} + v_{t+1}.$$

Note $E_t[v_{t+1}] = \gamma_1 [P_t - b_t - \alpha_1 b_{t-1} - \alpha_2 x_t^a - \alpha_3 x_{2t}] + \gamma_2 (P_t - P_{t-1} + b_t - b_{t-1})$.

The no-arbitrage condition: $E_t[P_{t+1} + d_{t+1}] = RP_t$ implies that

$$\begin{aligned} &(1+\alpha_2) E_t[x_{t+1}^a] \\ &= RP_t - (R+\alpha_1) b_t - \alpha_3 E[x_{2t+1}] - \gamma_1 [P_t - b_t - \alpha_1 b_{t-1} - \alpha_2 x_t^a - \alpha_3 x_{2t}] - \gamma_2 (P_t - P_{t-1} + b_t - b_{t-1}) \\ &= (R - \gamma_1 - \gamma_2) P_t - (R + \alpha_1 - \gamma_1 + \gamma_2) b_t + (\gamma_1 \alpha_1 + \gamma_2) b_{t-1} + \gamma_2 P_{t-1} + \gamma_1 \alpha_2 x_t^a - \alpha_3 E[x_{2t+1}] + \gamma_1 \alpha_3 x_{2t}. \end{aligned}$$

That is,

$$\begin{aligned} E[x_{t+1}^a] = {} & \frac{(R-\gamma_1-\gamma_2)}{(1+\alpha_2)} P_t - \frac{(R+\alpha_1-\gamma_1+\gamma_2)}{(1+\alpha_2)} b_t + \frac{(\gamma_1\alpha_1+\gamma_2)}{(1+\alpha_2)} b_{t-1} + \frac{\gamma_2}{(1+\alpha_2)} P_{t-1} + \frac{\gamma_1\alpha_2}{(1+\alpha_2)} x_t^a \\ & - \frac{\alpha_3}{(1+\alpha_2)} E[x_{2t+1}] + \frac{\gamma_1\alpha_3}{(1+\alpha_2)} x_{2t}. \end{aligned}$$

In terms of earnings, we have

$$\begin{aligned} E[e_{t+1}] = {} & \frac{(R-\gamma_1-\gamma_2)}{(1+\alpha_2)} P_t + \frac{\gamma_1\alpha_2}{(1+\alpha_2)} e_t + \frac{(R-1)\alpha_2 - 1 - \alpha_1 + \gamma_1 - \gamma_2}{(1+\alpha_2)} b_t \\ & + \frac{\gamma_1\alpha_1 + \gamma_2 - \gamma_1\alpha_2(R-1)}{(1+\alpha_2)} b_{t-1} + \frac{\gamma_2}{(1+\alpha_2)} P_{t-1} - \frac{\alpha_3}{(1+\alpha_2)} \{E[x_{2t+1}] - \gamma_1 x_{2t}\}. \end{aligned}$$

Let x_{2t} be operating cash flows at time t. Then abnormal growth of cash flows, $E[x_{2t+1}]-\gamma_1 x_{2t}$ can be viewed as accruals (acc_{t+1}). Note also that accruals are persistent, hence we can use accruals at time t to replace acc_{t+1} in our regression analysis. Denote $acc_t \equiv E[x_{2t+1}]-\gamma_1 x_{2t}$. The above model implies

$$E[e_{t+1}]=\frac{(R-\gamma_1-\gamma_2)}{(1+\alpha_2)}P_t+\frac{\gamma_1\alpha_2}{(1+\alpha_2)}e_t+\frac{(R-1)\alpha_2-1-\alpha_1+\gamma_1-\gamma_2}{(1+\alpha_2)}b_t$$
$$+\frac{\gamma_1\alpha_1+\gamma_2-\gamma_1\alpha_2(R-1)}{(1+\alpha_2)}b_{t-1}+\frac{\gamma_2}{(1+\alpha_2)}P_{t-1}-\frac{\alpha_3}{(1+\alpha_2)}acc_t.$$

Table 1: Sample Descriptive Statistics

Panel A: Summary Statistics

	eps	*afeps1*	*reps1*	*afeps4*	*p*	*bps*	*dps*	*asset*	*accrual*
N	149750	107217	130318	22344	149750	149750	149750	149750	136391
Mean	0.535	1.145	0.599	2.339	15.380	8.898	0.253	35.980	-0.943
St. dev	1.813	1.380	1.743	2.090	15.730	8.888	0.446	60.730	2.178
p25	0.021	0.380	0.045	0.970	4.957	2.959	0.000	5.989	-1.366
p50	0.508	0.900	0.551	1.890	10.470	6.239	0.013	14.700	-0.432
p75	1.256	1.680	1.313	3.200	20.120	11.880	0.325	37.500	0.002

Panel B: Correlation Matrix

	eps	*afeps1*	*reps1*	*afeps4*	*p*	*bps*	*dps*	*asset*	*accrual*
eps	1	0.850	0.758	0.656	0.615	0.575	0.510	0.532	-0.155
afeps1	0.668	1	0.804	0.811	0.720	0.668	0.529	0.640	-0.323
reps1	0.598	0.571	1	0.643	0.600	0.508	0.478	0.504	-0.245
afeps4	0.458	0.720	0.442	1	0.768	0.627	0.395	0.580	-0.312
p	0.370	0.572	0.349	0.708	1	0.624	0.342	0.516	-0.308
bps	0.384	0.569	0.279	0.549	0.583	1	0.460	0.863	-0.507
dps	0.396	0.472	0.365	0.351	0.390	0.515	1	0.561	-0.321
asset	0.243	0.363	0.223	0.348	0.300	0.554	0.383	1	-0.569
accrual	0.190	-0.137	-0.022	-0.231	-0.221	-0.347	-0.210	-0.337	1

The table reports summary statistics (Panel A) and the correlation matrix (Panel B) of the variables used in the empirical analysis. *eps* is net income before extraordinary items divided by number of shares outstanding. *reps1* is the one-year ahead realizations of earnings. *afeps1* and *afeps4* are the one- and four-year ahead analyst earnings forecasts. *p* is adjusted price per share of equity three months after the fiscal year end. *bps* is book value of equity per share. *dps* is common dividend per share. *asset* and *accrual* are also shown on a per share basis. Panel A reports the number of observations, mean, standard deviation, 25%, 50% and 75% quantiles. Firms in the extreme percentiles in earnings, book values, prices, *afeps1* and *asset* are deleted. Panel B reports the average annual cross-sectional correlations, with Pearson correlations in the lower half and Spearman correlations in the upper half.

Table 2: Earnings Model Estimation Results

	Const	p_t	e_t	$NegE_t$	b_t	b_{t-1}	p_{t-1}	acc_t	$Adj\text{-}R^2$
e_{t+1}	0.090	0.043	0.605	-0.149	-0.054	0.045	-0.029	-0.084	0.417
t-stat	5.91	18.25	31.03	-5.51	-5.60	4.84	-12.35	-9.07	
e_{t+2}	0.246	0.021	0.487	-0.159	-0.064	0.062	-0.014	-0.097	0.242
t-stat	12.32	6.42	22.52	-5.16	-5.34	5.13	-4.48	-9.32	
e_{t+3}	0.349	0.010	0.421	-0.176	-0.053	0.055	-0.006	-0.098	0.175
t-stat	16.11	2.60	17.79	-5.35	-3.77	3.95	-1.83	-8.84	
e_{t+4}	0.429	0.004	0.378	-0.205	-0.064	0.069	-0.002	-0.091	0.136
t-stat	18.45	0.58	15.99	-5.74	-4.72	5.08	-0.12	-7.45	
e_{t+5}	0.473	-0.001	0.375	-0.184	-0.064	0.070	0.003	-0.081	0.122
t-stat	20.24	-0.66	13.77	-5.09	-4.51	4.90	1.37	-6.42	

The table reports the average estimated coefficients, t-statistics (to test the null hypothesis that the coefficient in each case is equal to zero) and adjusted R-squared coefficients from the pooled cross-sectional regressions estimated each forecast year from 1976 to 2015, for the PW model:

$$e_{j,t+k} = \delta'_{0jk} + \delta'_{1jk} P_{j,t} + \delta'_{2jk} e_{j,t} + \delta'_{3jk} NegE_{j,t} + \delta'_{4jk} b_{j,t} + \delta'_{5jk} b_{j,t-1} + \delta'_{6jk} P_{j,t-1} + \delta'_{7jk} acc_{j,t} + \varepsilon_{j,t+k},$$

for k = 1-5, where $e_{j,t}$ is the earnings per share of firm j in year t, $P_{j,t}$ is the stock price, $b_{j,t}$ is the book value of equity and $acc_{j,t}$ is operating accruals on a per share basis. $NegE_{j,t}$ is a dummy variable that equals 1 if the firm has negative earnings at time t and 0 otherwise. The model is estimated for one-, two-, three-, four- and five-year ahead earnings. The two-sided critical values for the t-statistics at the 1%, 5% and 10% significance levels are, respectively, 2.576, 1.960 and 1.645.

Table 3: Forecast Bias and Accuracy

Panel A1: One-year ahead forecasts: bias and accuracy

	AR(1)	HDZ	PW	RW	IBES
Bias	-0.013	-0.005	-0.004	0.004	-0.040
Std. Dev.	0.114	0.111	0.107	0.131	0.124
Accuracy	0.065	0.063	0.060	0.068	0.063
Std. Dev.	0.106	0.102	0.100	0.129	0.122
N	87,309	87,309	87,309	87,309	87,309

Panel A2: One-year forecasts accuracy: t-statistics

	HDZ	PW	RW	IBES
AR(1)	17.79	43.38	-15.04	5.49
HDZ		34.48	-22.19	-0.46
PW			-36.92	-10.72
RW				12.71

Panel B1: Two-year ahead forecasts: bias and accuracy

	AR(1)	HDZ	PW	RW	IBES
Bias	-0.011	-0.001	0.000	0.015	-0.046
Std. Dev.	0.115	0.111	0.098	0.144	0.121
Accuracy	0.073	0.071	0.069	0.080	0.074
Std. Dev.	0.099	0.094	0.094	0.132	0.113
N	75,905	75,905	75,905	75,905	75,905

Panel B2: Two-year forecasts accuracy: t-statistics

	HDZ	PW	RW	IBES
AR(1)	17.72	43.25	-22.31	-3.07
HDZ		21.82	-29.55	-10.60
PW			-38.33	-18.72
RW				13.32

Panel C1: Five-year ahead forecasts: bias and accuracy

	AR(1)	HDZ	PW	RW	IBES
Bias	0.020	0.020	0.020	0.037	-0.049
Std. Dev.	0.109	0.106	0.105	0.150	0.110
Accuracy	0.073	0.070	0.070	0.084	0.078
Std. Dev.	0.093	0.088	0.086	0.137	0.099
N	10,058	10,058	10,058	10,058	10,058

Panel C2: Five-year forecasts accuracy: t-statistics

	HDZ	PW	RW	IBES
AR(1)	8.85	9.59	-12.59	-5.23
HDZ		-1.97	-15.02	-9.10
PW			-14.20	-8.65
RW				5.11

The left-hand panels of Table 3 report the average forecast bias (and standard deviation) and accuracy (and standard deviation) for earnings forecasts from the AR(1) model, HDZ model, PW model, RW model and I/B/E/S consensus forecasts as well as number of observations. Forecast bias is the average difference between realized earnings and forecast earnings, while forecast accuracy is defined as the average absolute value of the difference between realized earnings and forecast earnings. The right-hand panels of

Table 3 report the t-statistics to test the null hypotheses that the accuracy is equal between each pair of forecasts. The two-sided critical values for the t-statistics at the 1%, 5% and 10% significance levels are, respectively, 2.576, 1.960 and 1.645.

Table 4: Efficiency Tests

Panel A: One-Year Ahead Forecasts

	Const	*t-statistic*	*Slope*	*t-statistic*	R^2	*N*
AR(1)	-0.057	-1.49	1.119	3.06	0.378	87309
HDZ	-0.027	-0.88	1.075	2.50	0.391	87309
PW	-0.068	-2.01	1.068	2.64	0.416	87309
RW	0.251	6.9	0.630	-13.56	0.363	87309
IBES	-0.198	-5.48	0.786	-6.11	0.330	87309

Panel B: Two-Year Ahead Forecasts

	Const	*t-statistic*	*Slope*	*t-statistic*	R^2	*N*
AR(1)	-0.030	-0.53	1.078	1.29	0.205	75905
HDZ	0.029	0.77	1.009	0.19	0.228	75905
PW	-0.008	-0.2	1.044	0.86	0.228	75905
RW	0.383	7.49	0.479	-17.63	0.196	75905
IBES	0.038	1.01	0.495	-12.61	0.141	75905

Panel C: Five-Year Ahead Forecasts

	Const	*t-statistic*	*Slope*	*t-statistic*	R^2	*N*
AR(1)	0.524	4.29	0.989	-0.09	0.070	10058
HDZ	0.511	7.95	0.899	-1.30	0.104	10058
PW	0.486	7.74	1.029	0.35	0.094	10058
RW	1.039	10.61	0.289	-17.89	0.069	10058
IBES	0.690	10.39	0.255	-20.36	0.053	10058

The table reports the results of estimating the Mincer-Zarnowitz regression:

$$e_{j,t+1} = \alpha + \beta\,\hat{e}_{j,t} + v_{j,t+1}$$

for AR(1) forecasts, HDZ forecasts, PW forecasts, RW forecasts and I/B/E/S consensus forecasts. In each case, the table reports the estimated intercept and slope coefficients, t-statistics (to test the null hypothesis that the coefficient is equal to zero (for the constant) or equal to one (for the slope)), adjusted R-squared coefficient and sample size. The two-sided critical values for the t-statistics at the 1%, 5% and 10% significance levels are, respectively, 2.576, 1.960 and 1.645.

Table 5: Encompassing Tests

Panel A: One-year ahead forecasts (N = 87,309)

	Const	*t-statistic*	*AR(1)*	*t-statistic*	*HDZ*	*t-statistic*	*PW*	*t-statistic*	*I/B/E/S*	*t-statistic*	R^2
Model 1	-0.046	-1.29	0.321	3.41	0.783	9.88					0.393
Model 2	-0.077	-2.18	0.152	1.74			0.938	14.2			0.417
Model 3	-0.255	-9.07	0.758	13.95					0.391	8.84	0.420
Model 4	-0.073	-2.23			0.247	2.73	0.843	10.53			0.419
Model 5	-0.207	-7.4			0.756	16.02			0.351	8.36	0.422
Model 6	-0.221	-8.64					0.798	20.31	0.307	7.89	0.440
Model 7	-0.072	-2.01	-0.024	-0.25	0.263	2.56	0.849	10.21			0.419
Model 8	-0.229	-7.29	0.337	4.12	0.448	5.55			0.352	8.12	0.424
Model 9	-0.220	-8.42			0.112	1.17	0.703	9.12	0.300	7.4	0.441
Model 10	-0.223	-7.55	0.054	0.61	0.074	0.67	0.690	8.72	0.301	7.36	0.441

Panel B: Two-year ahead forecasts (N = 75,905)

	Const	*t-statistic*	*AR(1)*	*t-statistic*	*HDZ*	*t-statistic*	*PW*	*t-statistic*	*I/B/E/S*	*t-statistic*	R^2
Model 1	-0.007	-0.15	0.256	2.84	0.802	10.47					0.230
Model 2	-0.026	-0.52	0.179	1.77			0.891	9.8			0.227
Model 3	-0.169	-4.38	0.845	12.21					0.218	5.53	0.223
Model 4	-0.014	-0.34			0.540	7.07	0.522	6.31			0.235
Model 5	-0.085	-2.95			0.843	16.45			0.165	4.87	0.237
Model 6	-0.108	-3.75					0.876	15.79	0.157	4.42	0.235
Model 7	-0.012	-0.25	-0.018	-0.18	0.546	6.61	0.532	5.55			0.235
Model 8	-0.113	-3.02	0.221	2.58	0.669	9.68			0.161	4.62	0.239
Model 9	-0.103	-3.5			0.488	6.19	0.422	5.05	0.142	4.08	0.242
Model 10	-0.104	-2.86	0.010	0.1	0.485	5.85	0.416	4.3	0.142	4.11	0.242

Table 5: Encompassing Tests

	Const	*t-statistic*	*AR(1)*	*t-statistic*	*HDZ*	*t-statistic*	*PW*	*t-statistic*	*I/B/E/S*	*t-statistic*	R^2
Panel C: Five-year ahead forecasts (N= 10,058)											
Model 1	0.455	5.16	0.185	1.2	0.795	7.99					0.105
Model 2	0.480	5.96	0.033	0.15			1.004	5.95			0.094
Model 3	0.318	3.44	0.759	6.47					0.159	4.66	0.086
Model 4	0.417	6.53			0.593	7.8	0.455	4.01			0.110
Model 5	0.322	5.28			0.764	10.99			0.126	4.07	0.114
Model 6	0.302	4.92					0.856	11.01	0.131	4.73	0.106
Model 7	0.446	5.86	-0.169	-0.77	0.617	8.62	0.560	2.94			0.111
Model 8	0.303	3.87	0.081	0.57	0.722	8.01			0.122	3.98	0.114
Model 9	0.268	4.32			0.533	7.34	0.366	3.35	0.112	3.91	0.118
Model 10	0.303	4.17	-0.234	-1.13	0.564	8.14	0.509	2.79	0.116	4.07	0.119

The table reports the results of estimating the encompassing regression $e_{j,t+1} = \alpha + \beta_1 \hat{e}^1_{j,t} + \ldots + \beta_K \hat{e}^K_{j,t} + v_{j,t+1}$ for AR(1) forecasts and HDZ forecasts (Model 1), AR(1) forecasts and PW forecasts (Model 2), AR(1) forecasts and I/B/E/S forecasts (Model 3), HDZ forecasts and PW forecasts (Model 4), HDZ forecasts and I/B/E/S forecasts (Model 5), PW forecasts and I/B/E/S forecasts (Model 6), AR(1) forecasts, HDZ forecasts and PW forecasts (Model 7), AR(1) forecasts, HDZ forecasts and I/B/E/S forecasts (Model 8), HDZ forecasts, PW forecasts and I/B/E/S forecasts (Model 9) and AR(1) forecasts, HDZ forecasts, PW forecasts and I/B/E/S forecasts (Model 10). In each case, the table reports the estimated coefficients, t-statistics (to test the null hypothesis that the coefficient in each case is equal to zero), adjusted R-squared coefficient and sample size. The two-sided critical values for the t-statistics at the 1%, 5% and 10% significance levels are, respectively, 2.576, 1.960 and 1.645.

Table 6: Forecast Accuracy by Industry

Panel A: One-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10	11	12
AR(1)	0.063	0.069	0.069	0.085	0.046	0.072	0.061	0.029	0.064	0.055	0.062	0.072
HDZ	0.060	0.067	0.066	0.085	0.046	0.070	0.060	0.026	0.063	0.052	0.062	0.071
PW	0.056	0.062	0.062	0.077	0.042	0.068	0.059	0.025	0.061	0.052	0.059	0.068
RW	0.063	0.069	0.070	0.091	0.047	0.083	0.064	0.027	0.065	0.058	0.065	0.076
IBES	0.058	0.070	0.062	0.078	0.042	0.079	0.053	0.026	0.062	0.052	0.055	0.079
N	5,724	2,897	11,718	3,748	2,599	15,975	2,027	4,799	10,121	8,443	8,574	10,684

Panel B: Two-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10	11	12
AR(1)	0.069	0.080	0.081	0.100	0.057	0.077	0.064	0.033	0.071	0.063	0.069	0.080
HDZ	0.068	0.079	0.078	0.099	0.056	0.074	0.064	0.030	0.070	0.060	0.070	0.079
PW	0.064	0.075	0.074	0.093	0.052	0.073	0.063	0.029	0.067	0.060	0.067	0.077
RW	0.072	0.087	0.086	0.111	0.057	0.094	0.069	0.033	0.076	0.067	0.078	0.090
IBES	0.065	0.086	0.080	0.100	0.057	0.090	0.061	0.030	0.071	0.064	0.062	0.090
N	5,035	2,571	10,408	3,273	2,365	13,567	1,704	4,501	8,848	7,141	7,313	9,179

Table 6: Forecast Accuracy by Industry

Panel C: Five-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10	11	12
AR(1)	0.056	0.095	0.082	0.105	0.071	0.081	0.061	0.037	0.073	0.064	0.075	0.080
HDZ	0.054	0.085	0.079	0.110	0.067	0.078	0.064	0.038	0.073	0.062	0.080	0.078
PW	0.053	0.088	0.079	0.110	0.067	0.079	0.064	0.040	0.069	0.062	0.073	0.080
RW	0.061	0.107	0.095	0.112	0.077	0.098	0.079	0.041	0.079	0.073	0.102	0.102
IBES	0.060	0.105	0.091	0.117	0.066	0.091	0.065	0.032	0.077	0.084	0.065	0.102
N	573	238	1,050	656	336	1,347	411	1,231	1,038	1,274	947	957

The table reports the mean absolute forecast error of the AR(1), HDZ, PW, RW and I/B/E/S forecasts at the one-year horizon (Panel A), two-year horizon (Panel B) and five-year horizon (Panel C), for the 12 industries. The industries are 1 Consumer non-durables, 2 Consumer durables, 3 Manufacturing, 4 Energy, 5 Chemicals, 6 Business equipment, 7 Telecommunications, 8 Utilities, 9 Shops, 10 Healthcare, 11 Finance, 12 Other. N is the number of observations in each industry.

Table 7: Forecast Accuracy by Size

Panel A: One-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10
AR(1)	0.131	0.097	0.083	0.068	0.060	0.052	0.046	0.041	0.037	0.029
HDZ	0.130	0.098	0.082	0.069	0.060	0.051	0.045	0.040	0.035	0.028
PW	0.124	0.093	0.079	0.066	0.058	0.049	0.043	0.038	0.034	0.026
RW	0.149	0.107	0.087	0.072	0.062	0.053	0.047	0.040	0.036	0.028
IBES	0.148	0.104	0.082	0.068	0.057	0.048	0.041	0.035	0.030	0.022
N	8731	8731	8731	8731	8731	8731	8731	8731	8731	8730

Panel B: Two-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10
AR(1)	0.132	0.104	0.089	0.079	0.069	0.061	0.056	0.050	0.047	0.037
HDZ	0.132	0.104	0.087	0.079	0.069	0.060	0.055	0.048	0.046	0.036
PW	0.127	0.101	0.086	0.079	0.068	0.059	0.054	0.047	0.044	0.035
RW	0.163	0.120	0.097	0.086	0.075	0.064	0.058	0.050	0.047	0.037
IBES	0.149	0.113	0.093	0.083	0.069	0.062	0.055	0.046	0.041	0.031
N	7,591	7,590	7,591	7,590	7,591	7,590	7,591	7,590	7,591	7,590

Table 7: Forecast Accuracy by Size

Panel C: Five-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10
AR(1)	0.130	0.091	0.077	0.073	0.068	0.066	0.060	0.052	0.048	0.042
HDZ	0.124	0.089	0.076	0.069	0.067	0.065	0.058	0.052	0.049	0.043
PW	0.123	0.090	0.076	0.071	0.066	0.063	0.057	0.050	0.047	0.042
RW	0.173	0.111	0.090	0.082	0.074	0.078	0.068	0.060	0.056	0.048
IBES	0.163	0.102	0.086	0.079	0.067	0.068	0.060	0.056	0.052	0.045
N	1,006	1,006	1,006	1,006	1,005	1,006	1,006	1,006	1,006	1,005

The table reports the mean absolute forecast error of the AR(1), HDZ, PW, RW and I/B/E/S forecasts at the one-year horizon (Panel A), two-year horizon (Panel B) and five-year horizon (Panel C), for the 10 size deciles. N is the number of observations in each size decile.

Table 8: Forecast Accuracy by Earnings-to-Price (E/P) Ratio

Panel A: One-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10
AR(1)	0.212	0.052	0.025	0.026	0.027	0.028	0.032	0.041	0.056	0.089
HDZ	0.172	0.047	0.023	0.023	0.024	0.025	0.028	0.034	0.047	0.078
PW	0.122	0.030	0.017	0.012	0.011	0.012	0.014	0.019	0.028	0.048
RW	0.253	0.087	0.050	0.034	0.028	0.025	0.028	0.035	0.047	0.094
IBES	0.283	0.092	0.048	0.029	0.022	0.018	0.018	0.022	0.031	0.072
N	8,731	8,731	8,731	8,731	8,731	8,731	8,731	8,731	8,731	8,730

Panel B: Two-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10
AR(1)	0.148	0.079	0.059	0.046	0.043	0.044	0.049	0.059	0.074	0.104
HDZ	0.142	0.079	0.058	0.045	0.041	0.042	0.046	0.055	0.068	0.100
PW	0.126	0.073	0.056	0.042	0.037	0.037	0.040	0.047	0.060	0.088
RW	0.194	0.098	0.070	0.051	0.045	0.044	0.048	0.058	0.072	0.113
IBES	0.171	0.103	0.076	0.053	0.045	0.042	0.044	0.050	0.062	0.093
N	7,542	7,542	7,541	7,542	7,541	7,541	7,542	7,541	7,541	7,541

Table 8: Forecast Accuracy by Earnings-to-Price (E/P) Ratio

Panel C: Five-year Ahead Forecasts

	1	2	3	4	5	6	7	8	9	10
AR(1)	0.119	0.068	0.055	0.049	0.052	0.053	0.056	0.061	0.071	0.114
HDZ	0.112	0.067	0.056	0.049	0.054	0.053	0.056	0.060	0.070	0.113
PW	0.111	0.066	0.053	0.047	0.049	0.049	0.053	0.059	0.067	0.107
RW	0.189	0.079	0.061	0.053	0.059	0.059	0.059	0.064	0.073	0.134
IBES	0.149	0.092	0.068	0.062	0.056	0.058	0.055	0.061	0.067	0.105
N	991	990	990	990	990	990	990	990	990	990

The table reports the mean absolute forecast error of the AR(1), HDZ, PW, RW and I/B/E/S forecasts at the one-year horizon (Panel A), two-year horizon (Panel B) and five-year horizon (Panel C), for the 10 earnings-to-price (E/P) deciles. N is the number of observations in each E/P decile.